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Assessing the role of area sources in air quality: A comprehensive review

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Abstract

Air pollution poses significant challenges to environmental quality and public health. The array of factors contributing to air pollution necessitates a focus on three primary source categories namely point sources, mobile sources, and area sources. Point sources, typified by industrial facilities and power plants, emit pollutants from stationary positions, facilitating monitoring and regulatory interventions. Conversely, mobile sources including vehicles and aircraft, which emit pollutants while in motion, present a level of logistical challenges for control measures. Area sources, encompassing diffuse emissions from various activities such as agriculture, residential heating, and small-scale industry, present distinctive challenges in quantification and regulation due to their dispersed nature. Despite their substantial contribution to overall pollution levels, area sources have historically received less attention from researchers and regulators. The way to understand area sources is to use models for the other two, therefore, emphasizing the significance of studying area sources more comprehensively, this summary underscores the necessity of developing improved methodologies for assessing and mitigating their emissions.

Keywords: Area Air Pollution; Emission Sources; Diffuse Emissions; Source Apportionment; Emission Characterization; Spatial and Temporal Dynamics

1. Introduction

1.1. What makes air pollution a prominent subject of discussion?

Air pollution is a prominent subject of discussion due to its multifaceted ramifications on human health, environmental sustainability, and socioeconomic welfare. The socioeconomic implications of poor environmental management, particularly in regions like the Niger Delta, underscore the need for effective environmental policies to mitigate the impacts of pollution [1]. Pollution's pervasive presence and consequential effects have propelled it to the forefront of public discourse, scientific inquiry, and policy deliberations worldwide.

Primarily, the adverse health effects associated with air pollution have garnered widespread attention and concern, for studies have shown a rise in outdoor and indoor air pollution levels, focusing on its impact on respiratory allergies like asthma, and allergic rhinitis in the Asia-Pacific region [2] [3]. Additionally, there is a concern about the effects of PM2.5 exposure on mental stress and psychological well-being, highlighting the association between air pollution and public health [4]. The World Health Organization indicates that more than 6,000 cities across 117 countries are actively monitoring air quality, however, despite these efforts, numerous individuals remain subjected to elevated levels of air pollution[5], plus the need to industrialize quickly to alleviate poverty can exacerbate air pollution issues in these regions.

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The escalation of air pollution has become a subject of considerable concern, especially as its repercussions become increasingly evident with the advancement of technology and scientific exploration. These developments have enabled a more thorough understanding of the intricate facets of air pollution, which span industrial emissions, vehicle exhausts, and various residential and agricultural activities, however despite the essential role these activities play in human life [6], global endeavors such as the Paris Agreement emphasize the collective determination to address climate change, a challenge intricately linked with air pollution. Consequently, swift and concerted efforts are imperative from governmental bodies, industries, communities, and individuals alike to institute impactful measures and safeguard the health and welfare of present and forthcoming generations.

2. Introduction to Area Air Pollution Sources

Area source pollution, unlike emissions from specific point sources like industrial stacks or exhaust pipes, refers to the release of pollutants from multiple dispersed or non-point sources within a defined geographical area [7]. This includes various diffuse sources like residential heating, agriculture, transportation, and small-scale industrial activities, distinct and identifiable sources like factories or power plants, also broken down by country, region, and sector, accounting for different time patterns, including daily and hourly variations [8]. These diverse sources collectively contribute to the degradation of air quality, leading to various environmental and public health impacts. Unlike point sources, which are subject to strict regulatory controls and monitoring, managing area air pollution sources presents unique challenges due to their diffuse nature and the wide array of contributing activities. As a result, understanding the area's air pollution source is crucial for developing effective mitigation strategies, implementing regulatory frameworks, and safeguarding human health and the environment [9]. This introduction lays the foundation for exploring the complexities and implications of area air pollution sources in greater detail.

2.1. Types of Area Air Pollution Sources

Area air pollution source types vary reasonably depending on the nature of what makes the source therefore it is expedient to have a clear picture of what it entails as it is presented into three categories:

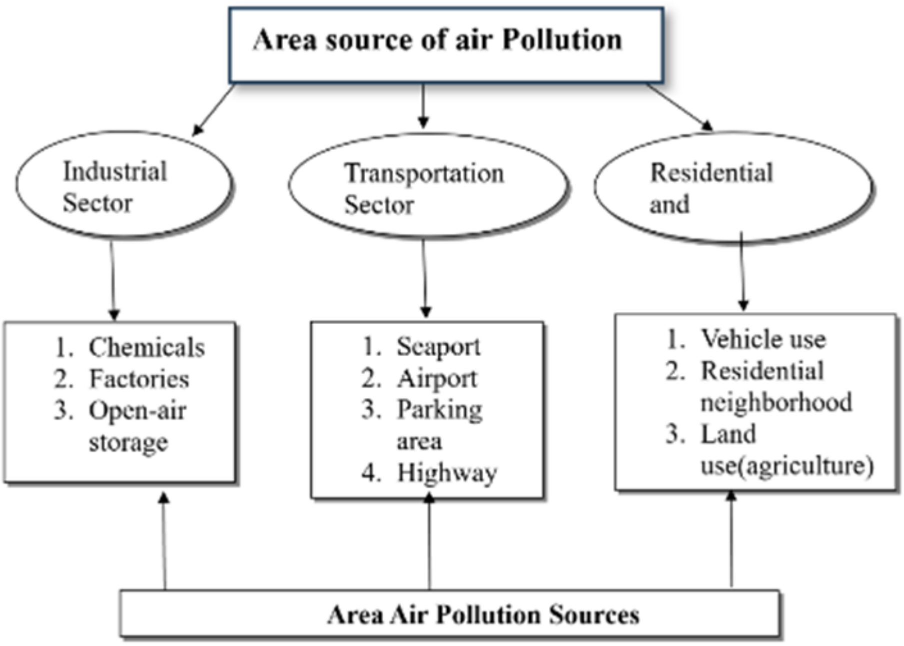

Figure 1 Area Air Pollution Sources

2.1.1. Industrial Sector

The focus is on the sub-emissions from an industrial complex, made up of multiple factories and facilities, storage and handling areas for raw materials or chemicals that emit pollutants continuously over a broad area [10], and lastly, the open-air burning or storage of bulk materials such as dioxins, coal or ore, leading to diffuse emissions [11].

2.1.2. Transportation Sector

The research indicates that emissions from a transportation hub such as a seaport, airport, or major highway interchange can be classified under an area air pollution source plus parking lots [12], with numerous vehicles collectively emitting pollutants in that specified area.

2.2. Residential and Commercial Sources

Overall emissions from a residential neighborhood, including combined sources such as heating, cooking, and vehicle use emissions [13], are coupled with emissions from a commercial district with multiple shops, restaurants[14], and office buildings and urban areas with mixed land uses emitting pollutants from various sources across a wide area[15].

Notably, area air pollution sources of any nature are most likely to be a collection and an ensemble of point sources or line sources viewed and analyzed over a certain area that ecloses them.

2.3. Current State of Knowledge

Overall, the current state of knowledge regarding area air pollution sources reflects a multidisciplinary and collaborative effort to advance understanding, mitigate impacts, and promote sustainable solutions for air quality management. The emphasis lies in emission characterization, where scientists strive to characterize and quantify emissions from area sources, including industrial complexes, transportation networks, and urban areas [16]. Advanced monitoring technologies, satellite observations, and modeling techniques are being employed to better understand the spatial and temporal patterns of pollutant emissions [17][18] through the use of an Infrared Atmospheric Sounding Interferometer (IASI) and Cross-track Infrared Sounder (CrIS). Additionally, efforts are underway in Emission Inventory Development to craft thorough inventories that encompass all pertinent sources of area pollution [19]. These inventories serve as crucial tools for air quality management, regulatory compliance, and policy development at local, regional, and global scales. Conversely, identification of the contributions of different pollution sources to ambient air pollution levels known as source apportionment utilizes advanced statistical techniques, receptor modeling, and chemical fingerprinting to distinguish between emissions from area sources, point sources, mobile sources, and natural sources[20], [21].

Current knowledge based on recent studies paves the way for impact assessment whereby scientists are investigating the environmental and health impacts of area air pollution sources on nearby communities and ecosystems [22]. Epidemiological studies, exposure assessments, and ecological monitoring provide insights into the effects of pollutants emitted from industrial facilities, transportation networks, agricultural activities, and urban development [23], as this knowledge informs risk assessment. The goal is to reduce the end-of-pipe dependency approach and apply front-of-pipe solutions where technological advancements to improve emission control devices, process optimization, alternative fuels, and renewable energy integration are employed. Additionally, land use planning, zoning regulations, and transportation policies are being explored as means to minimize exposure to pollution and promote sustainable development.

2.4. Research Gaps and Limitations

There is a significant lack of information and practical application when it comes to the research gap. This can be addressed by studying the limited knowledge available regarding the emission rates, composition, and temporal variability of pollutants from area sources. There is a need for an increased comprehensive study on spatial and temporal dynamics of air pollution to limit the environmental effects of pollutants emitted from area sources, lack of understanding of the chemical composition, physical properties, and atmospheric transformation of pollutants to determine tropospheric constituents[24].

The research endeavor into emission characterization and quantification faces considerable challenges stemming from the diverse nature of area sources. Obtaining accurate data proves difficult due to the sheer number of sources, including fugitive emissions and intermittent activities, leading to underestimated emissions. Furthermore, in the sector of spatial and temporal dynamics, researchers encounter obstacles in accessing high-resolution data and modeling tools necessary to capture local-scale variability and temporal trends, as a result integrating diverse data sources, such as ground-based measurements and satellite observations remains challenging, hindering improvements in spatial and temporal resolution[24]. An additional challenge is accounting for factors such as land use changes, meteorological conditions, and socio-economic activities that influence emission patterns [25].

One of the main difficulties is the inadequate spatial and temporal resolution of source apportionment techniques, which can lead to uncertainties when attempting to identify contributions from different sources [26], failing to distinguish between local and regional sources, as well as primary and secondary contributions to ambient pollution. To improve source attribution accuracy, it is essential to integrate multiple data sets such as emission inventories, atmospheric measurements, and receptor modeling results as B. Sauvage *et al* [27] describes the development of the SOFT-IO tool, which aims to quantify source-receptor links for measured data obtained from the In-service Aircraft for a Global Observing System (IAGOS) program. This tool utilizes the FLEXPART particle dispersion model and emission inventory data to simulate the contributions of anthropogenic and biomass burning emissions for all locations and times corresponding to the measured carbon monoxide (CO) mixing ratios along each IAGOS flight.

2.5. Technological and Methodological Challenges

Technological and methodological challenges associated with studying area air pollution sources pose significant hurdles to accurately characterize emissions since many area sources emit pollutants intermittently or at low concentrations, making it challenging to capture their emissions accurately. Developing cost-effective and portable monitoring technologies capable of quantifying emissions from diverse area sources in real-time remains a challenge and traditional stack testing methods designed for point sources may not be suitable for characterizing emissions from area sources for they are different. Spatial heterogeneity and temporal variability of emissions from area sources require high-resolution monitoring and modeling approaches to integrate data from multiple sources, such as ground-based sensors, satellite observations, and modeling outputs[28]. In addition, integrating multiple data sets and modeling approaches under source apportionment and attribution to ambient pollution to specific area sources with high confidence presents methodological challenges. Quantifying the cumulative effects and synergistic interactions between multiple pollutants emitted from area sources pose similar methodological challenges due to uncertainties in dose-response relationships and exposure pathways. Therefore, Mitigation Technology Development in integrating pollution control measures into existing infrastructure and industrial processes while minimizing energy consumption and economic costs is a necessity[29].

2.6. Emerging Trends and Innovations

Advancements in technology, particularly in Remote Sensing and Big Data Analytics [30], have streamlined the identification and monitoring of under-surveyed pollution sources. Through the utilization of satellite remote sensing and aerial imaging technologies, high-resolution mapping of area sources has become possible, allowing for real-time monitoring of air quality. Integration of big data analytics, machine learning, and artificial intelligence techniques allows for the processing and analysis of vast amounts of environmental data to identify pollution hotspots and trends. Low-cost sensor networks empower communities to monitor air quality and pinpoint local pollution sources, aiding targeted interventions[31]. Citizen science initiatives and crowdsourcing platforms involve the public in data collection, promoting community empowerment and environmental consciousness. The advancement of portable and mobile monitoring platforms facilitates convenient and real-time measurements of emissions from various area sources such as vehicles, industries, and construction sites. By combining sensor technologies with drones, unmanned aerial vehicles (UAVs), and autonomous vehicles, aerial monitoring of pollution sources becomes feasible even in remote or hazardous environments [32], [33]. Likewise, the integration of IoT sensors and smart city infrastructure enables real-time monitoring and management of urban air quality, traffic congestion, and industrial emissions [34].

2.7. Dispersion Modelling

Three different pollution sources require different approaches to analyze and solve, which includes the types of assumptions made. The following assumptions help streamline dispersion modeling for area air pollution sources but may introduce simplifications that affect the accuracy of predictions.

Homogeneous Emission Distribution is a common assumption for area sources that emissions are evenly distributed over the source area[8]. This assumption simplifies modeling by treating the entire area as a single emission point, neglecting variations in emission rates within the area but in reality, emissions from area sources can be heterogeneous due to factors such as activity patterns, equipment efficiency, and spatial layout.

Two-dimensional representation assumes that emissions spread uniformly in the horizontal plane (both x and y), neglecting vertical variations in concentration profiles or both (y and z axis) neglecting the advection x-axis direction of the wind and while suitable for many scenarios, this assumption may not capture the full complexity of dispersion in three-dimensional environments with complex terrain or atmospheric conditions [35].

Averaged Meteorological Conditions, sprout from the fact that meteorological characteristics need no human cause to happen, to a greater extent as a result of uncontrolled fluctuations, dispersion models typically use averaged meteorological data, such as wind speed and direction, temperature, and atmospheric stability over specific periods (e.g., hourly or daily averages))[36]. These averaged conditions may not fully capture the temporal variability of atmospheric parameters, such as diurnal changes in wind patterns or sudden shifts in weather conditions, which can affect pollutant dispersion patterns.

Steady-State Assumption, many dispersion models assume steady-state conditions, where emissions and meteorological conditions remain constant over the modeling period [37]. While this assumption simplifies calculations, it may not accurately represent dynamic atmospheric processes, especially during transient events like temperature inversions or sudden changes in wind speed but dispersion models are all statistically inclined (e.g. Box models - simplest dispersion models, which assume pollutants inside the box represent a given volume of atmospheric air in a geographical region and are homogenously distributed inside the box, Gaussian models – Gaussian Dispersion Models are based on determining the concentration of pollutant puff as it moves away from the source. A combination of infinitely rapid series of small individual puffs or plumes of polluted air has been considered for modeling purposes, Eulerian models – Eulerian model tracks the movement of a polluted plume through the fixed frame of reference, Lagrangian models – Lagrangian models follow the movement of individual particles as it moves in time and space. Advanced Dispersion Models – These models require three-dimensional meteorological fields and an assumption of spatial uniformity.)[37].

The uniform Surface Roughness approach across the entire area neglects variations in terrain, land use, and surface features that can influence atmospheric turbulence and dispersion patterns leading to inaccuracies in predicting pollutant concentrations, particularly in heterogeneous environments[38]. Validating model results against observed data and sensitivity analyses can help assess the impact of these assumptions and improve the reliability of dispersion simulations.

2.8. Equations

Given the difficulty of determining emission rates from area sources as depicted by the literature above, it is important to use different models to try and develop a solution-based approach with fewer errors. A few models are discussed mathematically below.

Point Source

The surface area when viewed from large distance x (m), tends to be applied as a point source where a certain model approach is used.

The emission concentration $C_{(x,y,z)}$ from a ground-level point source in a uniform unbounded airflow is given by Pasquil and Smith as:

$$C_{(x,y,z)} = \frac{E}{\pi\sigma_y\sigma_z u}.\exp\left(-\frac{y^2}{2\sigma^2{}_y}\right).\exp(-\frac{z^2}{2\sigma^2{}_z}) \qquad 1$$

Where E is the emission rate, x is the distance downwind to the point of reception(m), y is the distance crosswind (m) and z is the height above the ground(m). $\sigma_y$and σ_z represent "dispersion coefficients" in crosswind and vertical respectively(m), which are increasing functions of x and t, u is the wind speed (m/s). If the concentration at ground level (z = 0) from the ground level source is required the equation reduces to:

$$C_{(x,y,0)} = \frac{E}{\pi\sigma_y\sigma_z u}.\exp\left(-\frac{y^2}{2\sigma^2{}_y}\right) \qquad 2$$

The dispersion coefficients σ_y and σ_z in the absence of standard deviation of wind direction can be presented as functions of x as suggested by Bowers et al based-on Pasquil-Gifford curves as follows:

$$\sigma_y = 0.84678x\ .\tan(a - b\ln x) \qquad 3$$

and

$$\sigma_z = cx^d \qquad 4$$

Where a, b, c, and d are parameters that depend on the prevailing atmospheric stability with c and d being x dependent. Values of the four parameters a, b, c, and d are reproduced in Tables 2 and 3 according to Pasquill stability classification.[39]

Table 1 gives the meteorological conditions defining the Pasquill stability classes which showcases different reference points for deducing the parameters to be used.

Table 1 Meteorological conditions defining Pasquil stability classes ([39])

Surface wind speed (m/s	Day time Insolation			Night time conditions, thin, overcast or $\geq \frac{1}{2}\ \textit{cloudiness or} \leq \frac{3}{8} \textit{cloudiness}$	
	Strong	Moderate	Light		
<2	A	A-B	B		
2	A-B	B	C	E	F
4	B	B-C	C	D	E
6	C	C-D	D	D	D
>6	C	D	D	D	D

A: Extremely unstable conditions, B: Moderately unstable conditions, C: Slightly unstable conditions, D: Neutral conditions, E: Moderately stable conditions, F: Slightly stable conditions.

Table 2 Parameters in equation for crosswind dispersion (σ_z) for 1hr averaging time ([39])

Pasquill Stability Class	a	b
A	0.72722	0.044216
B	0.53814	0.031583
C	0.34906	0.018949
D	0.23270	0.012633
E	0.17453	0.009475
F	0.11636	0.006317

Table 3 Piecewise parameters in the equation for vertical dispersion (σ_y) ([39])

Pasquill Stability Class	Distance x	c	d
A	0-150	0.1087	1.0542
	150-200	0.08942	1.0932
	200-250	0.07058	1.1262
	250-300	0.03500	1.2644
	300-400	0.01513	1.4094
	400-500	0.002265	1.7283
	>500	0.0002028	2.1166
B	100-200	0.1451	0.93198
	200-400	0.1105	0.98332

	>400	0.05589	1.0971
C	All	0.1103	0.91465
D	0-300	0.08474	0.86974
	300-1km	0.1187	0.81066
	1-3km	0.3752	0.64403
	3-10km	0.5125	0.60486
E	0-300	0.08144	0.81956
	300-1km	0.1162	0.75660
	1km-2km	0.2771	0.63077
	2-4km	0.4347	0.57144
	4-10km	0.7533	0.50527
F	0-200	0.05437	0.81588
	200-700	0.06425	0.78407
	700-1km	0.1232	0.68465
	1-2km	0.1770	0.63227
	2-3km	0.3434	0.54503
	3-7km	0.6523	0.46490

2.9. Line Source of infinite length

To accurately describe emissions from an area source, it's crucial to account for emissions from different line and strip sources, particularly when the wind direction is perpendicular to the source, represented along the x-axis. The concentration at a height z and a distance x downwind from a source of infinite length is expressed as follows:

$$C_{(x,y,z)} = \frac{E}{\pi\sigma_y\sigma_z u}.\exp(-\frac{z^2}{2\sigma^2{}_z})\int_{-\infty}^{\infty}\exp\left(-\frac{y^2}{2\sigma^2{}_y}\right)dy \quad 5$$

Solution of the integral = $\sqrt{2\pi}\sigma_y$

Therefore, the equation becomes:

$$C_{(x,y,z)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{E}{\sigma_z u}.\exp(-\frac{z^2}{2\sigma^2{}_z}) \quad 6$$

And again, if the concentration is required at ground level the exponential term disappears and the equation reduces to:

$$C_{(x,y,z)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{E}{\sigma_z u} \quad 7$$

2.10. Line Source of Finite length

The concentration at distance x from the source and crosswind distance y from the center point of the source along the line of length Y is given as:

$$C_{(x,y,z)} = \frac{E}{\pi\sigma_y\sigma_z u}.\exp(-\frac{z^2}{2\sigma^2{}_z})\int_{y-\frac{Y}{2}}^{y+\frac{Y}{2}}\exp\left(-\frac{y^2}{2\sigma^2{}_y}\right)dy \quad 8$$

$$C_{(x,y,z)} = \frac{E}{\sqrt{2\pi}\sigma_z u}.\exp\left(-\frac{z^2}{2\sigma^2{}_z}\right).[\mathrm{erf}\left(\frac{y+\frac{Y}{2}}{\sqrt{2}\sigma_y}\right) - \mathrm{erf}(\frac{y-\frac{Y}{2}}{\sqrt{2}\sigma_y})] \quad 9$$

y = 0

$$C_{(x,0,z)} = \frac{E}{\sqrt{2\pi}\sigma_z u}.\exp\left(-\frac{z^2}{2\sigma^2{}_z}\right).[\mathrm{erf}\left(\frac{Y}{\sqrt{2}\sigma_y}\right)] \quad 10$$

Logically at $(x \leq Y)$, a short distance from the source, the finite and infinite line sources appear to be the same to the observer, it is only at greater distances that solutions start to diverge.

2.11. Strip Source of infinite Length

The strip of infinite length and width of length X from the center point of the source give the equation as follows:

$$C_{(x,y,z)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{E}{u}.\int_{x-\frac{X}{2}}^{x+\frac{X}{2}} \frac{1}{\sigma_z}.\exp(-\frac{z^2}{2\sigma^2{}_z})dx \quad 11$$

At ground level concentration becomes:

$$C_{(x,y,0)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{E}{u}.\int_{x-\frac{X}{2}}^{x+\frac{X}{2}} \frac{1}{\sigma_z}dx \quad 12$$

But

$$\sigma_z = cx^d \quad 13$$

Then:

$$C_{(x,y,0)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{E}{uc(1-d)}.[\left(x+\frac{X}{2}\right)^{1-d} - \left(x-\frac{X}{2}\right)^{1-d}] \quad 14$$

Concentration normalization through the introduction of $\emptyset_{(x,y,z)}$ where:

$$\emptyset_{(x,y,z)} = \frac{C_{(x,y,z)}.u}{E} \quad 15$$

Then equation 14 becomes:

$$\emptyset_{(x,y,0)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{1}{c(1-d)}.[\left(x+\frac{X}{2}\right)^{1-d} - \left(x-\frac{X}{2}\right)^{1-d}] \quad 16$$

Carney and Dodd assumed that the concentration from a strip source could be approximated by that from a line source (equation 6) multiplied by the strip width X, that is:

$$\emptyset_{(x,y,z)} = (\frac{2}{\pi})^{\frac{1}{2}}.\frac{X}{\sigma_z}.\exp(-\frac{z^2}{2\sigma^2{}_z}) \quad 17$$

2.12. Areal Source

An areal source is a wide strip of width X and finite length Y, the concentration from such a source would be given by the integration of equation 8 between the limits of $x+\frac{X}{2}$ and $x-\frac{X}{2}$. Given that σ_y and σ_z are both functions of x, the integration becomes more difficult if not impossible as a result there's a resolution to do it per strip.

$$\emptyset_{(x,y,z)} = \sum_1^n\{\frac{1}{\sqrt{2\pi}\sigma_{zi}}.\exp\left(-\frac{z^2}{2\sigma^2{}_{zi}}\right).[\,\mathrm{erf}\left(\frac{y+\frac{Y}{2}}{\sqrt{2}\sigma_{yi}}\right) - \mathrm{erf}(\frac{y-\frac{Y}{2}}{\sqrt{2}\sigma_{yi}})]\}\,\delta x \quad 18$$

where σ_{yi} *and* σ_{zi} refer to the ith strip of x_i distance from the receptor.

3. Discussion

The models employed to address various types of pollution sources that rely heavily on statistical methodologies, which inherently wrestle with the challenge of error quantification. Mathematically, equations can be adjusted to achieve specific objectives, through alterations and assumptions. In tackling the dispersion of pollutants from area, point, line, and strip sources, researchers have applied a variety of equations, each with its advantages and limitations. However, reconciling these diverse models presents a challenge as they offer distinct benefits and drawbacks. The point source model approach mainly assumes pollutants are emitted from a single point and dispersed in a Gaussian distribution with the advantages of being relatively simple and widely used to provide quick estimates of pollution concentrations.

Nevertheless, it is limited to point sources and may not accurately represent complex source geometries by not accounting for terrain features or nearby obstacles. The line and strip sources of infinite length depict emissions perpetually emanating from an endless line and a two-dimensional strip, respectively. Although both models possess similarities, allowing for the representation of linear sources like highways or continuous area sources such as urban areas and industrial zones, they simplify complex geometries. This simplification can result in potential inaccuracies, particularly when variations in source intensity along the line or strip are not accounted for. Line source of specific length offers more precise modeling of sources with defined boundaries and strip sources of limited length can account for variations in emission intensity along the strip but both may require additional parameters to accurately model the source. Despite their benefits, models are not infallible, they have their limitations. This is especially evident when dealing with area sources, which are diverse and present multiple challenges. This highlights the significant gap that still exists in achieving more accurate models.

Statistical methodologies that the models utilize in trying to handle different kinds of sources of pollution grapple with a fundamental problem of quantification of error. Mathematically, equations are modified and a number of assumptions are made in order to suit a certain objective i.e. on dispersion of pollutants from area, point, line, and strip sources, there have been numerous equations used by researchers, all with their merits and shortcomings. Again, these models are difficult to reconcile against each other, as each of them has various benefits and drawbacks. While the point source model approach is largely based on assuming that all pollutants are emitted from one point and then dispersed according to a Gaussian distribution, this has the advantages that it is relatively simplistic and also widely used in order to provide fast estimates of pollution concentrations.

Infinite line and strip sources are models of the same origin of the emissions but from a continuous infinitely long line and a two-dimensional strip respectively. These models are similar in nature, making the linear sources representative in applications such as highways and continuous area sources like towns and industrial areas, but they can be regarded as simple models of complex geometries. This can lead to some possible inaccuracies, especially where the intensity of the source changes along the line or strip. A line source of finite length will allow exact modeling of sources with well-defined edges, and strip sources of finite length will allow variability in emission intensity along the strip, but both might require additional parameters to model the source accurately. Models, despite their benefits, are not infallible, and they have their limitations. This is more obvious in the case of area sources, which are very diverse and give rise to multiple challenges. This shows a wide gap that still exists in the attainment of closer-to-reality models.

Compliance with ethical standards

Disclosure of conflict of interest

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